THE SCHMITTLETS FOR AUTOMATED SAR IMAGE ENHANCEMENT

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1. INTRODUCTION

Multi-looking is the essential step in SAR image preprocessing with respect to distributed targets. The presumably independent single intensity measurements of the same target are averaged in order to reduce the local variability and to retrieve a stable “mean” intensity for the target of interest [1]. In practice, multi-looking commonly is performed with a uniform number of looks all over the image though numerous studies already proofed that this is not suitable because signal of smaller targets possibly get mixed while larger targets are insufficiently smoothed. Thus, it is necessary to identify single targets, i.e. their location and their shape, to aggregate sample coming from the same main unit (statistically speaking). Three different approaches can be found in literature and in practice so far. Firstly, locally adaptive filtering techniques switch the filtering kernel of a fixed extension according to the local environment (multi-directional) [2]. Unfortunately, the extension of the local environment to be considered is uniform for the whole image. Hence, the scale of the targets of interest must be known in advance. Secondly, image segmentation aggregates neighboring pixels to segments of arbitrary shape according to homogeneity criteria (multi-directional and quasi multi-scale) [3]. The introduction of sharp edges between neighboring pixels, though very practical for computation, is not justified from an image processing perspective because a higher image resolution is feigned than existent. Furthermore, it denies the existence of mixed pixels in the single look image which are unavoidable due to the limited resolution of SAR images [4]. And thirdly, alternative image representations deliver an optimal multi-directional and multi-scale image description [5]. Evaluating the difference between neighboring scales of the image their application is restricted to images showing additive characteristics, i.e. a normal distribution as commonly accepted for optical images or logarithmic SAR intensities [6]. Therefore, this contribution introduces the Schmittlets as first alternative image representation (multi-directional, multi-scale, and multi-shape) that is applicable to SAR intensities in linear scale. Accordingly, it can easily be utilized for SAR image enhancement and SAR image analysis as well. The Schmittlet index layer indicating the best-fitting Schmittlet out of a selection of 35 geometric primitives for each location in the image gives valuable texture or structure information which can be used for scene characterization or classification purposes.

2. METHODOLOGY

The definition of the Schmittlets bases on the hyperbolic tangent function family employed for the normalization of intensity images and image combinations [7], for the description of random distributions in the context of change detection [8], and last but not least for the derivation of filter masks. In contrast to common alternative image representations using gradient operators, Schmittlets exclusively compose out of hyperbolic secant square functions to increase the stability of the analysis. Two different shapes of Schmittlets are predefined: round Schmittlets (equal look number for each direction) and lengthy ones (different look numbers per direction). Round Schmittlets can appear in different scales, i.e. different sizes. Lengthy Schmittlets can additionally adopt different orientations. In accordance with image processing theory the number of distinguishable directions increases from two in the second finest scale to sixteen in the fourth scale [9]. In this manner, 35 Schmittlets are defined from scale zero (original resolution) to scale four (sixteen looks per direction) which are depicted in Fig.1.

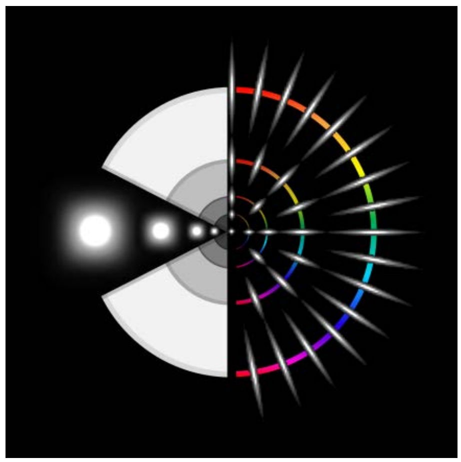

Figure 1: The 35 Schmittlets with different shapes (round on the left, lengthy on the right), different scales (concentric circles from fine inside to coarse outside), and different orientations (colors of the lengthy Schmittlets on the right)

At this point the image is scanned for the best-fitting Schmittlet by combining the original and the Schmittlet smoothed image in the hyperbolic tangent change measure and estimating the significance of the observed deviations by an empirically derived cumulative distribution function simulated according to a perturbation-based noise model. The best-fitting Schmittlet, i.e. the one showing the lowest significant deviation from the original, is selected locally. Large relatively homogeneous targets then are described by round Schmittlets in a higher scale. Smallest targets ranging near the image resolution are preserved in the finest scale. Lengthy structures are approximated by the lengthy Schmittlets in different scales, i.e. lengths, and orientations. The enhanced image finally is reconstructed out of the contributions of all best-fitting Schmittlets. Validation studies already proofed that this techniques excels standard methods in terms of preservation of the mean value, equivalent number of looks, and even edge preservation. Additionally, valuable structure information is provided [10].

3. APPLICATION

The potential of the Schmittlets is demonstrated in Fig. 2 visually. The original intensity image is geocoded using a pixel spacing of 1 m on ground, see Fig. 2a. This corresponds to the spacing of the single look image approximately. After applying the Schmittlet image enhancement (see Fig. 2b) strong structures, i.e. deterministic targets are still present in the best available resolution, but distributed targets are perfectly smoothed. The Schmittlet index layer containing the best-fitting Schmittlets can be found in Fig. 2c. Schmittlets are colored according to Fig. 1: dark for fine structures, bright for coarse structures and colors according to the direction. Fig. 2d shows an optical image of the site acquired at another time to get an impression of the surrounding.

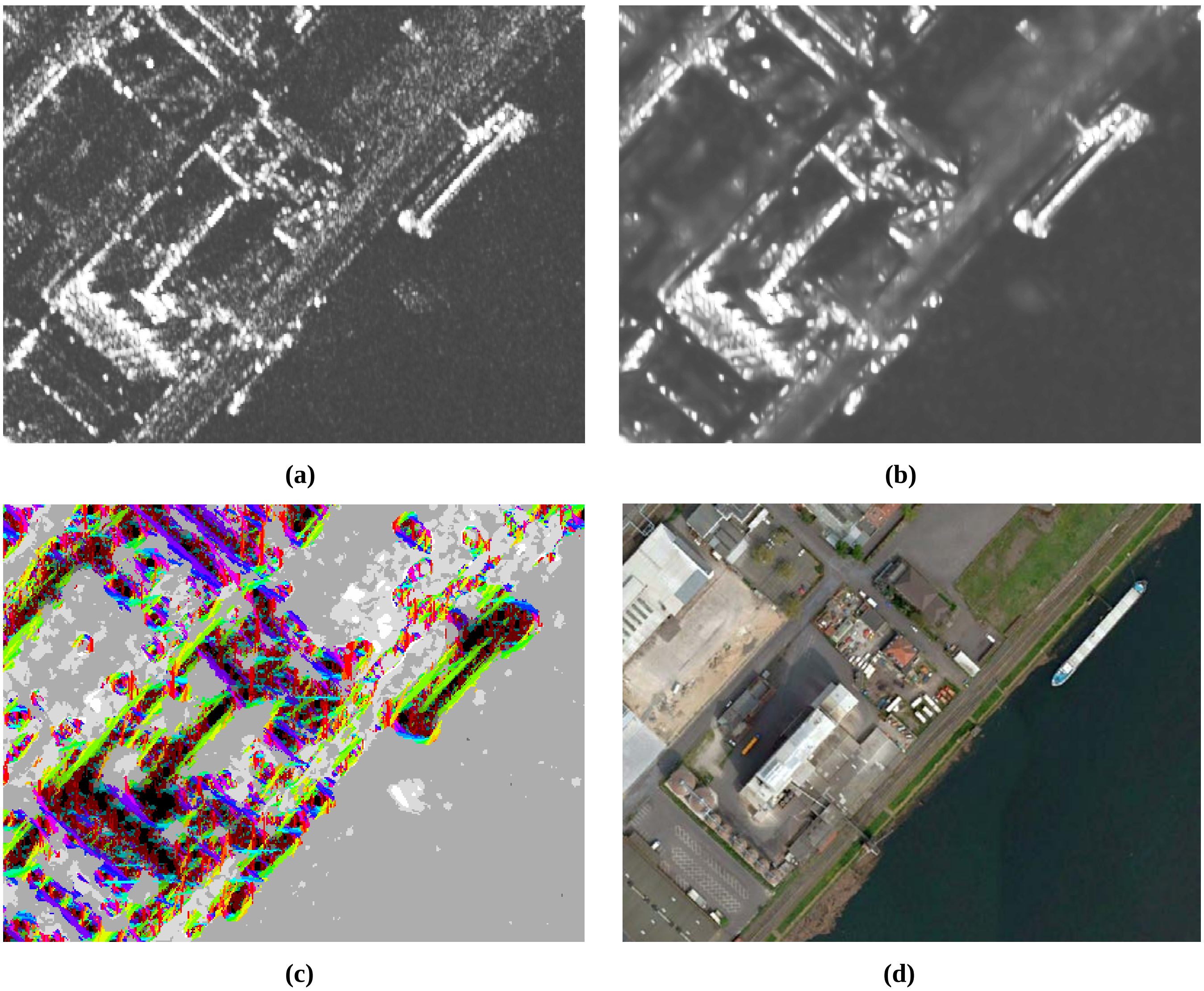

Figure 2: The products of the Schmittlets image enhancement for a TerraSAR-X high resolution spotlight image (©DLR, 2008) over the harbor area of Mannheim in southern Germany: (a) the original geocoded intensity image with a pixel spacing of 1 m and approximately 1 look, (b) the Schmittlet enhanced intensity image, (c) the Schmittlet index image with colors according to Fig. 1, and (d) an optical image of the test site (©GeoBasis-DE/BKG, 2014)

4. CONCLUSION

The Schmittlets represent a set of 35 geometric primitives proofed to be very suitable for the enhancement and the analysis of SAR intensity images. For each location in the image the best-fitting Schmittlet is selected via the significance of its deviation from the original image. Hence, the best-fitting Schmittlet guarantees minimal deviation from the original, but maximum equivalent number of looks without loss of edge information thanks to the novel perturbation-based noise model. The distinction of round undirected and lengthy directed Schmittlets delivers astonishing results in urban areas: distributed targets can be clearly identified while deterministic targets are additionally characterized by their size and their orientation. The Schmittlet index layer consequently contains very valuable texture information: the brightness refers to the scale and the color refers to the orientation of the underlying structures. The relative orientation in a certain environment (parallel, rectangular, diagonal, etc.) even allows conclusions about the urban structure type and might be brilliant data base for the characterization and the classification of urban areas from SAR imagery. Finally, the technique is designed and proofed to be able to proceed completely automatically and thus, it might possibly be implemented as standard SAR preprocessing.

5. REFERENCES

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